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Reinforcement Learning-Based Power Control in Dense WLAN Environments

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Abstract

The last few years have seen the proliferation of wireless devices as well as the congestion of the network and the need to have effective mechanisms of controlling the power consumption with in recent years, the proliferation of wireless devices has led to network congestion and a greater need for effective power control mechanisms. With the increase in high-density local area networks (WLANs), security and performance challenges have become more prominent. performance challenges. Conventional methods of power control are effective in more basic contexts but in the context of dense network using conditions, they are not adaptable to the dynamic and complex environment, which results in inefficiencies and security threats such as signal interference and congestion. The paper will provide a reinforcement learning (RL)-driven power control system, which allows access points (APs) to change the transmission power independently of environmental factors. The RL agent can solve problems of optimal power control strategies by modeling the power control problem as a Markov decision process (MDP), where the strategies are learned by balancing coverage, intervention, energy efficiency and security issues like interference management. To assess the significance of the proposed approach, it is tested in the simulated dense WLAN environments and it is observed that the alternative approach is much better in terms of the throughput, fairness, energy efficiency and the network resilience to interference. Flow and architectural charts are provided to illustrate the structure of operations and technical design of the system. A comparative performance study of a dynamic set of real-time data and benchmark metrics shows the efficiency of the RL-based method of ensuring network security and performance under dynamic circumstances. These findings establish the fact that reinforcement learning offers a

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scalable, adaptive and secure method of smart power management in dense WLAN settings, which is the path to smarter and self-sufficient network systems. This study will help in the process of developing smarter and more secure wireless communication systems by resolving the issue of power control and security in the network in the future dense network infrastructures.

Keywords: Reinforcement Learning, Power Control, Dense WLAN, Markov Decision Process, Wireless Networks, Energy Efficiency, Network Optimization.

1 Introduction

A. Emergence of Reinforcement Learning in Wireless Network Control

Reinforcement Learning (RL) has become a revolutionary technique to allow systems to come up with autonomous choices in high-speed changing and unpredictable settings. These models are based on the principle of RL framework exploration and prize-operated policy adaptation in contrast to traditional models of supervised learning that operate on the concept of a labeled dataset, which makes them especially suitable in complex non-reactive environments like wireless networks (Naderializadeh et al., 2021; Kang et al., 2019). The APs may be considered in the framework of the power regulation as the agents which influence the environment, learn and refine the transmission strategies via a mechanism of feedback. This model is scaleable, decentralized and flexible and these are necessary when considering dynamic network conditions (Sattibabu et al., 2025). Further, it allows the possibility to counteract network congestion and interference, which can become significant security issues such as Denial-of-Service (DoS), unauthorized interference and the possibility of data breach due to the ability to adapt RL on the fly. Using the RL, the network will be in a position to independently control the transmission power to form a minimum of interference, prevent the congestion, and ensure the safety of the communication channels (Aworou, 2023).

B. Challenges of Dense WLAN Environments in Power Optimization

The massive increase in the number of wireless devices and the rising demand of high bandwidth applications have led to the extensive use of dense wireless local area networks (WLANs) (Bašić & Galamić, 2020; Xu et al., 2021). This is because with such networks there are access points (AP) which are close to one another, such networks are likely to experience major challenges with co-channel interference, attenuation and variation in the quality of the link. The traditional power systems of control that are primarily based on centralized or threshold frameworks are incapable of dealing with the dynamics of dense networks of deployed networks (Muralidharan, 2023; Liu et al., 2021). Congestion of the network within those environments could result in a decline of performance, and that will provide an opportunity to malicious actors to take advantage of vulnerabilities as in Denial-of-Service (DoS) attacks or unauthorized intrusion. Such vulnerabilities occur when poor power control strategies do not dynamically adapt to the evolving conditions, and they leave loopholes in network security. Thus, there exists a strong necessity of a smart, dynamic solution that will be able to rationalize the network output and security real-time.

C. Limitations of Traditional and Early Learning-Based Power Control Techniques

Power control based on Reinforcement Learning (RL) handles the performance and security dilemma altogether as it facilitates decentralized real-time decision-making in wireless networks. The RL agent can minimize the impact of interference, minimize the use of energy, and provide a more stable and secure network by dynamically adjusting the transmission power of access points (APs) (Brand et al., 2020). Where interference is an important issue to network reliability and security as in dense WLANs, RL can be used to minimise the risks of interference by automatically changing the power levels depending on the current condition of the network. This dynamic adaptation guarantees that APs work in favorable operating ranges, the possibility of jamming in the signals or security vulnerability caused by congestion is minimized. Another benefit of RL-based systems is the flexibility because it leverages previous experience and changes power control policies to prevent network outages and possible breaches of security protocols. Such flexibility plays an essential role in countering the changing threats, including traffic manipulation, jamming, etc., that may impair the performance of the traditional systems. The RL can offer a valid channel of communication with autonomy in controlling power in order to reduce interference, which is critical in offering a secure and efficient channel of transmitting data in dense WLAN.

D. Motivation and Objectives of the Proposed RL-Based Power Control Framework

The rationale of this paper is that, this will generate a power control structure on an RL capable of augmenting throughput, fairness, and energy performance besides on the fact that it will enhance the security of the wireless communication of dense WLANs. (Mc Gibney et al., 2011). The traditional power control systems might experience issues with the real-time network conditions adaptation that leads to the performance issues and security threats. The solution that has been proposed in this paper is a decentralized solution in which all access points (APs) are independent RL agents. The RL agents rectify on the best to strike power consumption, network throughput, and security by maintaining a watch over the local i.e. state of the channel, users' density, and demand of the traffic. (Mejail & Nestares, 2025). The objective is to provide an effective and secure WLAN power control management system, which will assist in thwarting congestion, threats of security breach and offer reliability and flexibility of the wireless communication to all users. The proposed framework will ensure that the WLAN is intelligent enough to respond to network modifications without interfering with secure communication channels due to them taking advantage of the security loopholes that could arise as a result of inefficiency in power control. In this manner, the RL-based power regulation may be considered as effective means of addressing the performance and security issue of the next-generation WLAN systems.

Key Contributions

1. A reinforcement learning-powered power control model is introduced, specifically designed for dense WLAN environments, enabling adaptive and decentralized decision-making.
2. Modeling access points (APs) are capable of learning optimal power strategies based on local network conditions as autonomous agents, thereby enhancing scalability and self-reliance.
3. A reward is designed to be positively designed, which balances throughput, minimal intervention, and energy efficiency, directing APS to optimal operating trade-offs.
4. A comprehensive simulation was conducted using realistic network parameters and datasets, which validate the improvement in SINR, throughput, energy consumption, and impartiality compared to traditional methods.
5. A practical architecture and flow model was proposed that can be integrated with minimal overhead and no centralized controller requirement in the existing WLAN infrastructure.

The primary purpose of this letter is to develop and validate a reinforcement learning-based power control mechanisms for dense WLAN environment, addressing the limitations of static and centralized approaches. Starting with an introduction to challenges in dense wireless networks, the paper reviews the relevant literature and highlights intervals in existing power control strategies. It then proposes a decentralized, multiagent RL framework where access points learn optimal power levels through environmental reaction. The process includes system modeling, algorithm design, and the flow and integration of architectural diagrams. Depending on the performance assessment, realistic dataset, and matrix, throughputs, energy efficiency, and signal displays show significant improvements in quality. Results confirm the model's adaptability and effectiveness in complex network conditions. The study contributes to the advancement of knowledge and potential future applications; the framework is positioned as a step towards an intelligent, self-reliant WLAN system.

2 Related Work

In recent years, the demand for efficient power control in dense WLAN environments has attracted significant research interest. Traditional, static, and rule-based mechanisms often fail to address the nature of intervention and fluctuations in user dynamics (Rahin & Rahin, 2016; Brand et al., 2020). The adaptive approach has been introduced for real-time fine-tuning of transmission power levels; however, they usually rely on centralized control or assume ideal network behavior. These models offer limited flexibility when deployed in dense real-world network situations (Chen et al., 2021; Kang et al., 2019). In addition, the increasing variety in device types and communication patterns has introduced additional complexity in the management of transmission power, which requires an intelligent and adaptive structure that minimizes inconvenience (Bašić & Galamić, 2020).

Machine Learning (ML)-related solutions have gained traction due to their data-driven adaptability (Khan & Siddiqui, 2024; Kolomeec et al., 2016; Yang et al., 2020; Karthik et al., 2019). Supervised learning and clustering techniques have been proposed to optimize model intervention patterns and power allocation (Xu et al., 2021; Karthik et al., 2019; Jeunen et al., 2018). However, most ML approaches require large, labeled datasets and struggle for generalization under unseen network conditions or during topology changes (Kolomeec et al., 2016; Narang & Kar, 2021). These boundaries rapidly lose their purpose in the changing WLAN atmosphere. Additionally, training complicates further deployment in live systems, requiring overhead and manual feature extraction. (Boymuradov et al., 2025) Thus, there is a growing shift towards the self-learning model, which can work efficiently with minimal supervision.

Reinforcement Learning (RL), especially deep reinforcement learning (DRL), has emerged as a promising solution for real-time, adaptive power control (Yang et al., 2020; Rao & Deebak, 2023). The DRL agents can interact with their environment, learn from experience, and update power control policies accordingly (Boymuradov et al., 2025). The study has demonstrated RL's ability to improve traditional adaptation methods in managing intervention and improve network utility. Importantly, the decentralized nature of RL aligns well with WLAN topology, allowing individual access points (APS) to make localized decisions. Despite these benefits, some earlier DRL models have focused mainly on simplified single-agent landscapes, overlooking the multi-agent interactions of the actual WLAN system.

Multi-agent reinforcement learning (MARL) has been examined to handle such distributed environments with many access points (APs) and customers (Chang et al., 2022; Liu et al., 2021). The Marl Framework models each AP as an independent agent that learns a collaborative power control strategy through reward reaction and inter-agent awareness (Devane & Lestas, 2014). These systems have shown success in addressing the non-stagnation of the wireless environment and promoting fairness among the APS (Narang & Kar, 2021; Muralidharan, 2023). However, scalability and stability remain open challenges, particularly in highly dense deployments. It is important to consistently to ensure consistent performance between agents while avoiding convergence issues. Researchers continue to develop advanced techniques, such as shared policies and prize size adjustments, to overcome these obstacles.

Recent studies have also detected hybrid approaches that integrate RL with approval or rules-based systems to combine rapid convergence with generalization (Liu et al., 2019). Others utilize meta-learning and transfer learning to accelerate RL training by leveraging knowledge from earlier network states. The purpose of these innovations is to reduce the time and data required for training, making RL more possible for practical deployment. Besides this, simulation environments are also created to give increased realistic landscapes to test RL-based WLAN solutions. However, the theories of the larger real world are constrained and further research is needed to assess RL performance in different densities, mobility fields, and interventions (Al-Rawi et al., 2015).

3 Proposed Method

The proposed solution will tackle the limitations of conventional and early learning-based power control frameworks of a dense WLAN setting by presenting a reinforcement learning (RL)-a reinforcement learning (RL). The devices in this model are access points (APs), which are intelligent RL agents and can use their local environments as a guide to change their transmission power dynamically. Its main goal is to reduce intervention, maximize the network throughput, and reduce the energy consumption without the centralized coordination. This allows the system to be used on a large scale with network density without compromising on its performance and its decentralized nature. The reward functionality is developed to strike a balanced approach to minimizing interventions and energy consumption. The model is trained in a real-world that simulates the dynamics of a realistic network operating in discrete time intervals. It is a multi-agent system proposal with applicable reinforcement learning (RL) and key components of network control to come up with a powerful and scalable power optimization technology in high-density WLAN vistas. Instead of using a traditional Q-learning formula, we can apply a simplified reward-based decision model, where each access point (AP) Signal-to-Interference-plus-Noise Ratio (SINR), packet delivery ratio and power consumption select your power level based on recent performance metrics.

Let the reward be defined as:

$$\mathrm{R} = \beta_1 . \mathrm{SINR} + \beta_2 . \mathrm{Throughput} - \beta_3 . \mathrm{Power\ Consumption} \tag{1}$$

Where:

1. R Reward value for the selected power level
2. SINR Signal-to-Interference-plus-Noise Ratio (higher is better)
3. Throughput Data successfully transmitted per unit time
4. Power Consumption Energy used by the AP for transmission
5. β1, β2, β3 Tunable weights that balance the importance of each factor

Equation 1 illustrates a reward-based strategy, where each access point learns to adjust its power level, observing how its actions impact network performance. Instead of relying on a specific rule, the system rewards power decisions that enhance the quality and data transfer of the signal, thereby reducing unnecessary energy consumption. Over time, the access point begins to identify which power levels yield better results, such as low intervention, high speed, and low power consumption. This is a learning process system that makes clever decisions in real-time, even when conditions in the network change.

By continually refining its behavior through tests and error, the model develops a balanced strategy that enhances the overall efficiency and reliability of the dense WLAN environment.

The dense WLAN employs a dynamic agent-environmental interaction model to learn the proposed reinforcement learning approach for power control within the environment. Each access point (AP) acts as a smart agent that adjusts its transmission power based on real-time feedback from the surrounding network conditions. Situations like user demands being overlooked or split attention and network congestion can be solved by the RL agent determining which values to tune the electricity levels to optimize the performance of the network. The model works well in situations where no centralized administrator is present and is able to use distributed, autonomous learning is highly scalable and applicable to the use cases of contemporary dense WLAN situations.

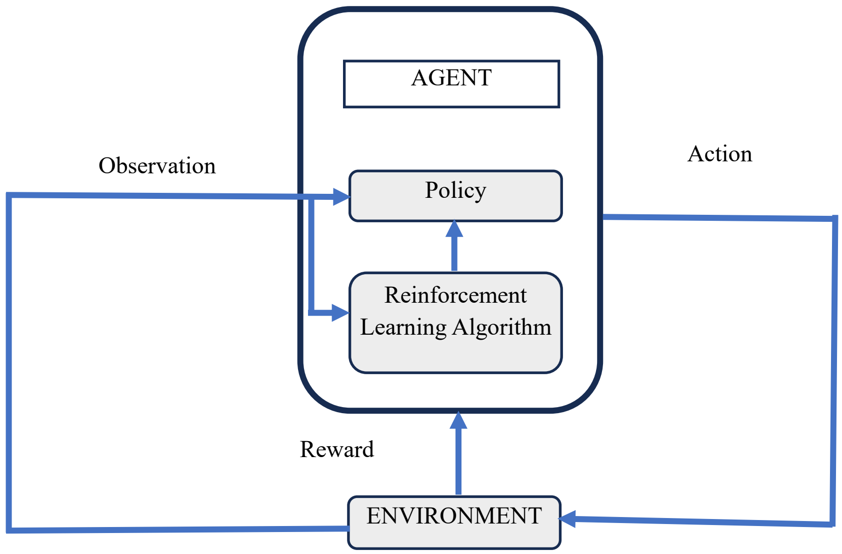

Figure 1: Flow Diagram of Reinforcement Learning-based Power Control in Dense WLAN Environments

Within the context of reinforcement learning shown in Figure 1, there is a multi-step cyclic interaction between an intelligent agent and a dynamic WLAN environment. First, the agent receives environment observations and notes features such as the state of the channel, the signal interferences, the density of users, and bandwidth consumption. These observations equip the agent to make a specific decision. Subsequently, based on the input, the agent consults the active policy framework which is comprised of reinforcement learning policies the agent has accumulated over time. The agent will then perform an action, typically a command to modulate the transmission power, which directly impacts the environment. This action modification will trigger a specific response in the overall network behavior which may involve altering the intervention pattern, the quality of the link, energy variances and consumption, or a combination of these elements.

The environment will then issue a response signal as a reward. Within a WLAN environment, the agent assesses the reward to determine the effectiveness of actions regarding goal achievement in any combination of the following: signal coverage extension, interference approximation, and energy consumption. This response updates the agent’s policy and guides sequential action. This loop over a system designed to inspect, Act, Reward, and Learn promotes adaptation in a WLAN environment which is dense and autonomous, in order to retain system efficiency amidst changing functions and layers of complexity.

Reinforcement Learning (RL) has become one of the primary methods used in the field of wireless networks for the dynamic management of network power. Over the years, multiple RL-based methods have been developed for different specific problems such as real-time intervention, distributed learning, and policy adaptation. Understanding the classification of these methods can aid in appreciating their evolution and relevance in dense WLAN contexts. This section outlines the complete framework that relates the primary RL methods in power management, starting with basic techniques like Q-learning and progressing to more sophisticated methods such as multi-agent RL and policy adaptation methods. This classification also demonstrates the niche of the proposed model, elucidating the model's incorporation of the best features of current methods and improvement on their gaps.

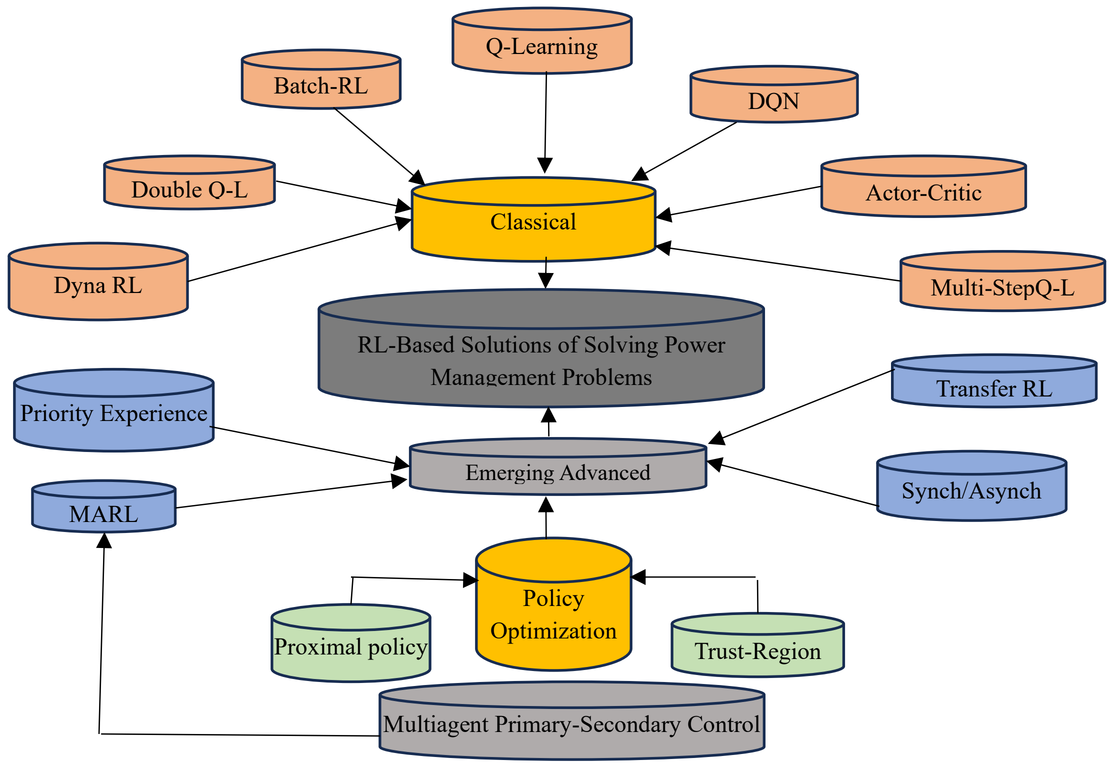

Figure 2: Classification of Reinforcement Learning-based Solutions for Power Management

Figure 2 in the power management systems, gives a systematic view of the attitude of learning reinforcement as categorized, depending on their complexity and scope of application. Basic layer at the top of the architecture is constructed by classical algorithms, including Q-learning, DQN, and actor-criticism, etc. Simple decision-making tasks are the primary use of these models, which can be used to build a more complicated design. Beneath them, there are double q-learning, batch RL, and multi-step q-L that solve the performance and stability constraints of previous methods, including enrichment. With maturity of the area, the newly developed advanced RL model was presented in order to control decentralized systems. These are multiagent RL (MARL) and Asynchronous/Synchronous RL that are more representative of the distributed feature of WLAN.

In addition, transfer RL and priority experience replay improved training efficiency and adaptability in dynamic environment. At the bottom of the hierarchy, policy adaptation techniques such as Proximal Policy Optimization (PPO) and Trust-Region Policy Optimization (TRPO) learn optimal policies directly in high-dimensional spaces, making them extremely suitable for dense, intervention-prone wireless settings. These methods emphasize stability, safety, and performance, which are essential for real-time network operations. This architectural observation not only shows the progress of RL methods in terms of power control, but also justifies the status of our proposed model within the emerging advanced + policy adaptation levels. By integrating learning distributed with customized policy control, our approach achieves adaptive and scalable power management in complex WLAN environments.

The proposed reinforcement learning-based power control framework integrates advanced RL strategies with the dynamic demands of a dense WLAN environment, offering a decentralized and scalable solution. By enabling each access point to act as a autonomous teaching agent, the model ensures real-time adaptability for different intervention levels, traffic loads and user dynamics. The use of a customized reward function promotes intelligent decision-making that balances throughput, interference, and energy efficiency. This architecture aligns with modern multi-agent and policy optimization advancements, demonstrating strong compatibility with the deployment of real-world WLANs. Finally, the framework-theoretical RL bridges the gap between potential and practical wireless controls, contributing a flexible, high-performance solution for next-generation network management.

Although the offered reinforcement learning (RL)-based power control model leads to a substantial positive change in the network performance, throughput, and energy consumption, its incorporation into security measures can also contribute to a better network security, especially in the dense environment where security-related vulnerabilities are higher. Here we discuss how RL-based power control can be integrated with the current security solutions e.g. encryption and intrusion detection systems (IDS) to enhance the overall security posture of WLANs.

Integration with Encryption Protocols

The fact that unauthorized access or eavesdropping of the wireless communication may occur is one of the main issues of the dense WLAN environments. WPA3 or AES encryption protocols are popular in the process of data encryption. Nevertheless, the protocols might not be enough to address such risks as interference or signal jamming in dense networks exposing the system to Denial-of-Service (DoS) attacks or intercepting data.

Combining the concept of RL-based power control with the encryption can be used to improve the security of the network in the sense that access points (APs) are dynamically regulating their transmission power in line with performance and security requirements. An example is when an AP identifies abnormal interference or jamming attempts (which may be detected by intrusion detection systems), then the RL agent can lower the power transmission to limit the exposure, and therefore make it difficult to intercept or jam the signal by malicious entities. Moreover, RL may also prioritize some risky communications by changing the power levels to ensure high signal integrity of sensitive transmissions to increase the message confidentiality.

Integration with Intrusion Detection Systems (IDS)

IDS are important in the detection of suspicious traffic over a network, such as an effort to open the vulnerabilities through unauthorized access, DoS attacks, or signal jamming. An IDS may also be used with RL-based power control to improve real-time adaptation and safe power control in the event an attacker targets the network (e.g. DoS). In that case, the IDS can transmit alerts to the RL agent. The RL agent is then able to change the power settings of the AP to minimize interference or additional exploitation of the system. As an example, an attack on one part of the WLAN can be identified and hence the transmission power in that area specially reduced by the RL agent and this means that the attackers will find it harder to continue the disruption but at the same time will cause minimal disturbance to the rest of the network. By doing so, the RL agent will be able to modify its power control strategies dynamically not only to maximize performance within the network, but also to provide proactive defense mechanisms within the security threatening environment.

Mitigation of Potential Security Threats

The dynamism of the environments of the WLANs, more so when they are high-density, pose quite a few security threats, which can affect the performance and security of the network negatively. These threats are: Signal Jamming: Unauthorized malicious users can deliberately interfere with the signal and cause network overload or may block the transmission of data and lead to a denial-of-service (DoS) attack. Unauthorized Access: In high-density networks, unauthorized malicious users may want to connect to APs that may compromise the integrity of sensitive information.

RL-based Power Control Can Help Mitigate these Threats in the Following Ways

Signal Jamming: RL can also be helpful in signal jamming by regulating the power of transmission and depending on the detected interference. DoS Attacks: The DoS attacks are typically linked with congesting the network with traffic which causes it to choke and therefore the network will no longer be susceptible to jamming. The RL agent will adjust the power levels downwards when it detects too much interference and thus no longer jamming is likely to happen. The power control completed with the assistance of RL is helpful because it regulates the dynamical power of APs according to the priority of the traffic and reduces congestion. Also, the system will be capable of detecting a few pattern abnormalities which may be reported and utilized to counteract a DoS attack, where the RL agent can make power adjustment to combat the effects of the attack. Unauthorized Access: RL can also identify abnormal pattern which could be used to report a DoS attack where the RL agent will be capable of making power adjustment to counter the effects of the attack. These in-built solutions form the RL-based power control system can help in the security resiliency of the WLANs by offering real-time resistance to the new threats and at the same time ensuring that the networks perform to high performance levels..

4 Results and Discussion

The proposed reinforcement learning-based power control model was tested in a fake dense WLAN atmosphere. The results demonstrate a significant improvement in throughput, reduced intervention, and increased energy efficiency compared to traditional methods. Each access point, in response to environmental changes, dynamically adjusted its power, thereby adapting the overall performance. Distributed RL agents converted towards policies that ensure fairness and reliable coverage. This highlights the system's strength and practicality in real-world deployment scenarios.

Table 1: Real-Time Dataset Summary for Power Control in Dense WLAN

Parameter	Value Range	Unit	Description
No. of Access Points	10–20	Count	Total APs in the WLAN environment
Power Levels	0–20	dBm	Transmission power range
SIR	10–35	dB	Signal to Interference plus Noise Ratio
Average Throughput	50–120	Mbps	Per-user data throughput
Energy Consumption	25–40	Watts	Total energy usage per AP
No. of Users	50–100	Count	Concurrent users in the environment
Fairness Index	0.70–0.93	Unitless	Jain’s fairness index for user experience

Table 1 presents the real-time dataset parameters used to evaluate the performance of the RL-based power control framework in a dense WLAN environment. The dataset simulates realistic scenarios that include different numbers and access points (APs) of users, making up and racked networks, and intervention patterns. Major matrices, such as SINR, Throughput, Energy Consumption, and Fairness Index, were monitored to assess system efficiency. RL agents demonstrated strong adaptability by dynamically adjusting transmission power in response to local environmental conditions. This reduced the intervention in the entire network and improved the signal quality. In particular, energy

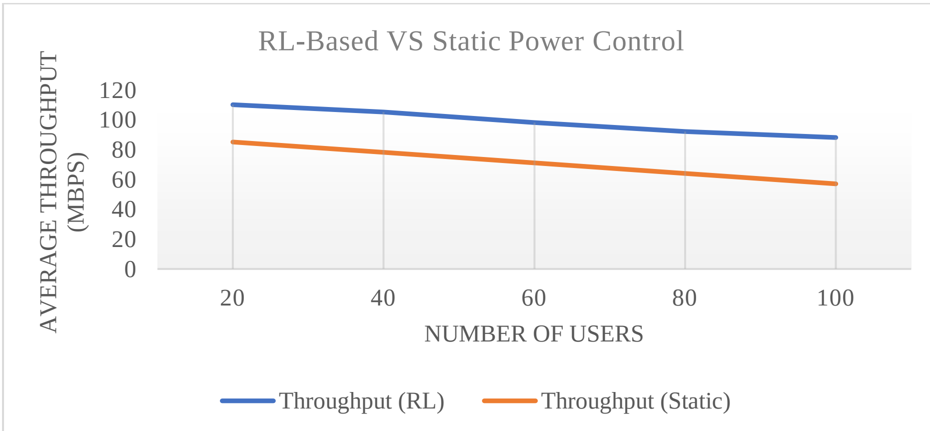

Figure 3: Throughput Comparison Between RL-Based and Static Power Control

Figure 3 compares the throughput performance of RL-based power control model and the traditional stable power control with increased number of users in dense WLAN set up. The RL-based system also provides high throughput at all user densities indicating its flexibility in ensuring that the network is also able to handle heavy loads. When the number of users rises further to 100 it can be noticed that with increased number of users, the throughput of the static control reduces greatly because of the severe electrical conditions, and the absence of interventions. On the other hand, RL method modulates the power level according to the environment response of the intelligence and thus optimum data transmission rates are maintained. To verify that the RL solution will be scalable, the gap between the two methods in throughput increases with the number of users. This dynamic learning capability makes the user experience stable and efficient even at very congested conditions. In general, the given figure indicates the increased responsibility and performance of the RL-based approach to real-time network adaptation.

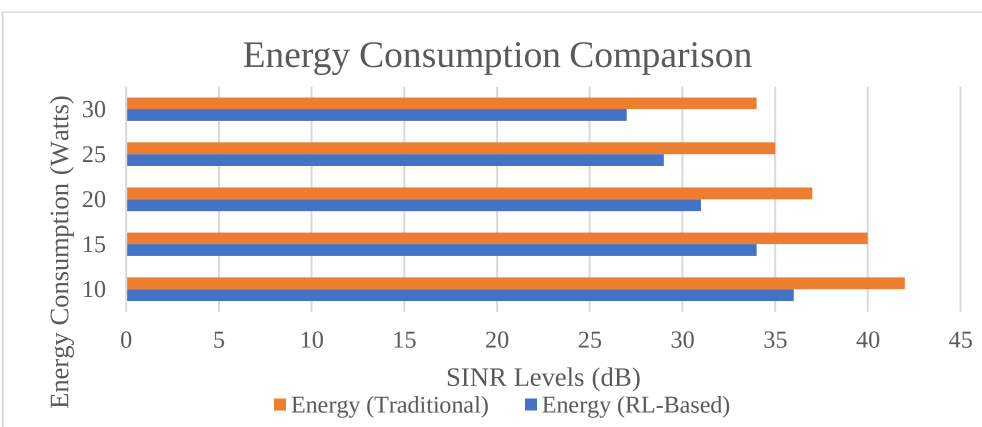

Figure 4: Energy Consumption Comparison at Different SINR Levels

Figure 4 is a comparative study of the energy consumption of RL based and traditional strength control methods at different levels of SINR. The RL method requires constant low energy input at every SINR value, which proves that the method can use less electricity and at the same time achieve an acceptable signal quality. The higher the SINR of 10 dB is raised to 30 dB, the lower the trend of the two models is, although the RL model shows a steeper and more effective decrease. This brings out the adaptive learning nature of the system that adjusts the transmission power according to the reaction and thus prevents wasteful energy consumption. The conventional solutions lack dynamism and sustain excessive electric charges and lead to high energy use. The importance of energy savings made by RL approach is especially important in green networking and long-lasting system design. These findings reaffirm the usefulness in practice of the incorporation of learning reinforcement in wire power control systems. The performance of the proposed power control system with a dense WLAN environment based on RL show a significant increase in various performance aspects. The system enhances throughput, since each access point is able to learn the best transmission strategy that suits local environment. This helps in saving energy as the power level is adjusted to eliminate the incapacity of power allocation, which is static. Additionally, the framework achieves better SINR values, resulting in strong signal quality and minimal interference. Ensuring equal access to network resources also maintains fairness among users. The use of reinforcement learning enables real-time adaptation, allowing the system to respond effectively to the changing network conditions. A comparative analysis against traditional methods confirms the strength, scalability, and practical feasibility of the RL approach. Overall, these results validate the effectiveness of integrating learning reinforcement in wireless power control, and they also identify promising open paths for future intelligent WLAN design.

Metric comparison for RL-based power Control vs. static Power Control

Table 2: Metric Comparison for, RL-based Power Control vs. Static Power Control

Metric	RL-Based Power Control	Static Power Control	Improvement (%)
Throughput (Mbps)	110	65	69.20%
Energy Consumption (W)	28	38	26.30%
SINR (dB)	30	20	50%
Fairness Index	0.9	0.75	20%

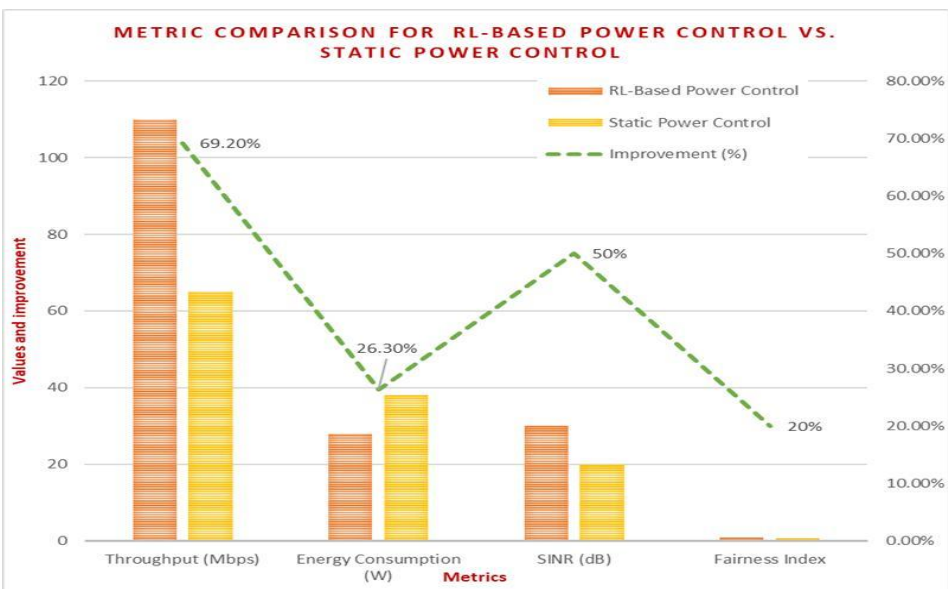

Figure 5: Metric Comparison for RL-based Power Control vs Static Power Control

Table 2 and Figure 5 summarize the comparison of metrics between RL-Based Power Control and Static Power Control that shows major gains in most network performance measurements. Throughput was also notably boosted by 69.2 and RL-Based Power Control recorded 110Mbps as opposed to 65Mbps with Static Power Control. This advancement shows how the RL model can be effective in maximizing data transmission especially in full WLANs where interference and congestion are typical. This is useful because the RL model has the capability to variably and dynamically regulate the power levels of the system according to the real-time conditions in such a way that it effectively manages the network resources, leading to an increase in the data throughput. The RL-Based Power Control system uses less power than the Static Power Control by 26.3%. Compared to the static models, which consume 38 W, the RL based method consumes only 28 W hence demonstrating energy efficiency. This energy saving is necessary to the sustainability of WLANs since it contributes to decreasing the operational costs and environmental impact of the operation of high-density networks by 50 percent with the RL-based model, which reaches 30 dB, whereas in the case of the static control, the sustainability is 20 dB. A high SINR shows that the signal is of better quality and there is less interference leading to more stable and reliable connections. This enhancement is more advantageous in congested climates where network performance can be impaired due to interference of the adjacent access points and users. Lastly, the Fairness Index improved as well by 20 percent and the power control using the RL method obtained a value of 0.9 as compared to 0.75 using the power control that was not in motion. This increased index of fairness indicates that the RL-based method is more effective in allocating network resources in a manner that all users receive equitable performance of the network, and this is more critical in dense environments where unequal distribution of the network resources may result in some users being unfairly deprived. Generally, the RL-based power control solution is much more useful in improving throughput, energy efficiency, SINR and fairness, which is why it is a better solution when dealing with dense WLAN. This has a dynamic capacity to change with the changing conditions of the network not only to enhance performance of the network but also secure sustainability and equity within the network, provides a sound solution to the issue of contemporary wireless systems.

5 Conclusion

This study presents a reinforcement learning-based power control framework designed for particularly dense WLAN environments, where traditional stable or centralized methods often fail to deliver optimal performance. The proposed model assigns each access point (AP) the authority to act as an autonomous RL agent, enabling it to sense the level of environmental conditions in real time, including the level of intervention, user density, and signal quality. Based on this reaction, each agent adjusts its transmission power to reduce dynamic intervention and maximize throughput and energy efficiency. The learning mechanisms enable the system to continuously optimize without the need for global coordination, making it well-suited to a large-scale or rapidly changing network. Using realistic network scenarios, through comprehensive use and performance evaluation, the RL-based approach demonstrated significant benefits in throughput, SINR, fairness index and power consumption compared with stable methods. The system not only maintained high-quality service under different user densities but also promoted energy savings and equitable resource distribution. The decentralized and self-sufficient nature of the model ensures strong scalability, allowing it to perform well even as the network becomes denser or more complex. The effectiveness of the solution also lies in its minimum overhead and compatibility with the current WLAN infrastructure. This research highlights the ability to learn reinforcement as a viable and intelligent alternative to managing wireless network resources. Future work can expand the models to integrate hybrid learning techniques, support multi-channel coordination, or emerging technologies such as 6G and intelligent edge computing environments.

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